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Inside the Black Box: Understanding key drivers of global emission scenarios

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ABSTRACT

Technology and policy implications of global energy and emissions scenarios can be difficult to analyze because underlying assumptions and drivers of scenarios are rarely made explicit. This article documents methods for standardizing emissions scenario results that can be applied to virtually any scenario, enabling more meaningful comparisons among scenarios than has been possible in the past.

This approach uses charts showing the dynamics and effects of emission drivers, mitigation technologies, and policies. Applying these methods will enable the policy and research communities to better understand the implications of scenarios, and help analysts learn more rapidly. As a matter of good practice, modelers should create decompositions like the ones put forth in this article, policy makers should request them, and funders of scenario analysis and sponsors of model comparisons should support the application and further development of such tools.

1. Introduction

After the COP23 meetings in Bonn in November 2017, the policy community is increasing its focus on reducing greenhouse gas (GHG) emissions quickly and efficiently. To understand the range of possible solutions, scientists have for many years used Integrated Assessment Models, which attempt to assess the costs and benefits of climate action. Many researchers have raised analytical concerns about these models and associated methods (Ackerman et al., 2009; DeCanio, 2003; Koomey 2012, 2013; Pindyck 2013, 2017; Rosen and Guenther, 2015) but they provide a systematic way to track the implications of possible scenarios, and we'll no doubt need accounting tools like them to explore future scenarios that are potentially promising.

Energy scenarios explore a range of conditions possible in an inherently uncertain future, including the responses to policy interventions that could stabilize atmospheric greenhouse gas concentrations (Riahi et al., 2017). Because the future is deeply uncertain, it is appropriate to analyze any single energy and emissions scenario in the context of other cases, such as a family of scenarios generated by a single model (WBGU, 2004), a set of models generating a common scenario (Weyant, 2004), or a diverse selection of scenarios in the literature (Hamrin et al., 2007). To compare the insights within and between these types of studies, an effective and consistent framework for interpretation is essential (Hummel, 2006).

Unfortunately, different practices for reporting scenarios in the literature make it difficult to compare results and infer their meaning. Policy analysts, who are often a primary audience for scenario results, then face the challenge of interpreting and evaluating a steady stream of studies based on different models and baseline assumptions. The importance of addressing this and related challenges has led to calls for greater transparency, disclosure, and self-examination by the energy modeling community (for example, Koomey et al. (2003) and Pfenninger (2017)).

This article describes one technique with minimal data requirements that can be used to illuminate technology and policy implications of global, regional, or country-level energy and emissions scenarios for a policy audience. This technique uses "driver dashboards" of line graphs that make explicit the relative role of key drivers of emissions over time in a particular scenario. After reviewing these dashboards, a researcher can put the quantitative results of each scenario into context and compare the results to historical trends and to other scenarios presented in the same framework.

The factors in the first dashboard include population growth, economic activity, final and primary energy consumption, and total fossil carbon dioxide emissions from the energy sector. The second dashboard shows ratios of these terms. The third dashboard displays total

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projected energy sector emissions as well as emissions and reductions from biomass sequestration, land use, industrial non-energy CO_2 emissions, and other warming agents. Supplemental graphs yield additional insight.

To describe and demonstrate the utility of this interpretive technique, this article first reviews a commonly used method for scenario decomposition (the Kaya identity) for the energy sector and then describes why an expanded version of this method is required. Section 3 describes in more detail methods for creating such an expanded decomposition. Next, the article expands the analysis further to include sources of emissions reductions outside the energy sector. It then describes use cases for such decompositions, focuses on limitations of the analysis, suggests areas of future research, and summarizes the conclusions that emerge from this analysis.

2. Building on a familiar concept: the Kaya Identity

The decomposition presented here is adapted and expanded from a well-established convention in emissions scenario analysis known as the Kaya Identity (Kaya, 1989), which is commonly used to decompose drivers of greenhouse gas emissions in the energy sector. As many researchers have realized over the years, the Kaya identity as it was originally introduced is incomplete. This section reviews the original Kaya Identity and how it has been used (and altered) in the past, then modifies and expands the decomposition to correct for the issues in earlier formulations.

2.1. Overview of the Kaya Identity

The Kaya Identity illustrates the key drivers for fossil carbon dioxide emissions from the energy sector. This identity decomposes carbon emissions as a product of aggregate wealth, energy intensity of economic activity, and carbon intensity of the energy supplied. As originally presented (Kaya, 1989), it reads as shown in Equation (1):

$$\text{Carbon emissions} = \frac{E}{GNP} \cdot \frac{C}{E} \cdot GNP \tag{1}$$

where

GNP = gross national product, a measure of economic activity;
$\frac{E}{GNP}$ = primary energy intensity per dollar of GNP, and
$\frac{C}{E}$ = carbon intensity of primary energy production

Professor Kaya presented this equation to help understand the implications of history and future scenarios in a simple “back of the envelope” way.

In most uses of this equation, the order of the terms is switched, so that aggregate wealth is first, energy intensity is next, and carbon dioxide intensity (rather than carbon intensity) of primary energy supplied is third (IPCC, 2014, p.368). Most analysts split the aggregate wealth term into terms focused on population and economic activity per person, which leads to the more familiar “four-factor” Kaya identity in Equation (2) (note different variable abbreviations than in Equation (1)):

$$\text{Carbon dioxide emissions} = P \cdot \frac{GWP}{P} \cdot \frac{PE}{GWP} \cdot \frac{C}{PE} \tag{2}$$

where

P is population;
GWP is gross world product, a measure of economic activity;
PE is primary energy, including conversion and energy transmission losses;
C is total net carbon dioxide emitted from the primary energy resource mix;
$\frac{GWP}{P}$ is the average income per person;
$\frac{PE}{GWP}$ is the primary energy intensity of the economy; and
$\frac{C}{PE}$ is the net carbon dioxide intensity of supplying primary energy.

In its substance and structure, the Kaya identity reflects a more general identity that expresses impact (I) as a product of human population (P), affluence (A), and technology (T) (Ehrlich and Holdren 1971, 1972). Population is the same in both the Kaya and IPAT identities, GWP/person represents affluence, and the other two terms characterize technology.

This formulation implies that a larger number of people with a higher income and more extensive use of certain technologies will have a greater impact on the environment. The role of technology can be ambiguous – technologies that produce and combust fossil fuels are the primary anthropogenic source of carbon dioxide, while technologies for harnessing renewable energy and nuclear power, sequestering carbon, and improving efficiency can reduce net anthropogenic carbon emissions.

2.2. Previous uses of the Kaya Identity in scenario analysis

The Kaya Identity has been widely used, with some prominent examples being Nakicenovic et al. (2000), Kawase et al. (2006), Raupach et al. (2007), and Hoffert et al. (1998). There are so many examples, in fact, that we don't attempt a comprehensive review here. What is interesting is that there's been only modest progress in the use of this identity since 1989, beyond the initial expansion of the identity to split population from GWP per person. Some researchers have expanded the identity to account for other weaknesses as we discuss below, although those efforts always stopped short of what we term our “expanded Kaya identity” for the energy sector presented below.

To explore the intellectual history of this concept, Appendix A examines how five generations of reports for the Intergovernmental Panel on Climate Change (IPCC) and related reports have treated the Kaya identity. The IPCC reports represent the state of scientific understanding about climate change at any time, so they are a good marker for evolution in the understanding and use of this concept in analyzing historical data or in evaluating future scenarios.

In no case did the IPCC reports expand the Kaya identity beyond its slightly expanded four-factor form as shown in Equation (2), above, but the Assessment Reports became more sophisticated over time in how they used the concept and presented the analysis results. Other researchers have expanded the identity, but progress on this front has been piecemeal and halting. Appendix A also presents the key articles that made progress in expanding the identity over time.

2.3. Reasons to expand the decomposition

2.3.1. Disentangling energy intensity and supply chain losses

The most widely used metric for energy intensity of economic activity (PE/GWP) refers to primary energy (PE), which is the total energy input to the economy from all sources, measured as the energy potential in fossil fuels and biomass at the point of extraction (Grübler et al., 2015). The PE/GWP metric is sensitive to four types of changes in an energy-economy system, each of which is affected by specific dynamics outlined with examples in Table 1.

Although the definition of energy intensity as a ratio of primary energy to economic activity (PE/GWP) is widely used in the literature, there are long-standing arguments for separating final energy to better assess trends in end-use demands and to isolate the first effect (energy supply losses) in Table 1 (Schipper et al., 1992). Final energy is the energy that is actually delivered to the customer's meter or gas tank, and it can include electricity, gasoline, hydrogen, or direct uses of natural gas, coal and biomass (Grübler et al., 2015). The Special Report on Emissions Scenarios (SRES) reports Final Energy (FE) in its detailed

Table 1
Energy-economy dynamics that affect the ratio of primary energy to GWP.

Category	Cause	Example
Energy Supply Losses in supply chain from primary to final energy	Technological improvements in the efficiency of energy supply conversion Changes in the balance of demand for final energy sources Interfuel substitution among primary energy sources supplying each final energy type	A shift toward cogeneration of heat and electricity A rising share of final energy from electricity A rising share of electricity generated using natural gas
End-use Efficiency in the conversion of final energy to end-uses	Technological improvements in the efficiency of end-use energy conversion Interfuel substitution among final energy sources	More efficient lights or motors A shift from all-gasoline to plug-in electric hybrid vehicles
Structural Change in the economy	Changes in the modes of energy service delivery Changes in the types of economic activity	Globalized trade patterns; Urban development patterns A rising share of economic activity from the services sector
Conservation	Reduction in non-productive energy uses	Carpooling; Changes in personal behavior or lifestyle

appendices, allowing a more accurate assessment of the energy intensity of the economy (Nakicenovic et al., 2000), and a few analysts have disaggregated FE/GWP and PE/FE in previous scenario decomposition studies (Grübler et al., 1993; Kawase et al., 2006; Price et al., 2006).

Following those authors, the PE/GWP metric can be further disaggregated as shown in Equation (3):

$$\frac{PE}{GWP} = \frac{FE}{GWP} \cdot \frac{PE}{FE} \tag{3}$$

where

$\frac{FE}{GWP}$ is the Final Energy Intensity of Economic Activity, and

$\frac{PE}{FE}$ is a measure of total energy system supply losses for delivering final energy to users.

The ratio of primary energy to final energy delivered at an economy-wide scale indicates the portion of potential energy lost in the supply chain. A value of 1.0 indicates zero conversion losses in delivering final energy to users, so this ratio will be greater than 1.0 for all real energy systems.

In the context of a single technology type (e.g. an electric power plant), the ratio of final energy to primary energy (FE/PE) is a metric that captures both the efficiency of conversion and efficiency of energy transport/transmission. At an aggregate data level, however, it is not accurate to represent the ratio of primary energy to final energy (PE/FE) as the inverse of the conversion efficiency, as is done, for example, in Kawase et al. (2006). Table 1 lists three different dynamics in an energy system that can affect supply losses, and a change in technical efficiency is only one.

Energy supply losses do occur as a result of some inefficiency along the way, but the value of the metric itself varies even if conversion efficiencies in the system are held constant. Changes in the PE/FE ratio can result from changes in the balance between fuels supplying a single type of final energy (e.g. natural gas vs. coal for electricity generation) or the balance between final energy types (e.g., supplying water heating using electricity or natural gas). For the sake of precision and clarity this article departs from the system efficiency terminology used by some other authors in favor of the more precise term Energy Supply Loss Factor (ESLF).

2.3.2. Converting non-combustion energy production to primary energy

One of the key issues in understanding energy systems is assessing the total energy consumed by the system, including all the losses in making energy available to consumers. This assessment is complicated because of variations in how different energy sources produce fuels or electricity that allow us to do useful work.

Primary energy is the energy contained in fossil and biomass fuels, measured as (for example) the heat content of coal that goes into a power plant's boiler (Grübler et al., 2015). The difference between primary energy and secondary energy is the conversion loss in converting coal to electricity. The secondary energy is the amount of electricity injected into the grid at the busbar (measured in kWh), which also called net generation (after accounting for on-site use of electricity to run the plant). Final energy is the electricity delivered to the customer's meter, which is lower than that injected by the power plant into the grid because of transmission and distribution (T&D) losses.

Nuclear, hydroelectric, solar electric, wind power, and other non-combustion sources of electricity (or hydrogen or process heat created using these fuels) do not have losses that result in additional emissions like fossil fuel generation does. What should define the quantity of primary energy for these sources? There is the energy embodied in the nuclear fuel and the solar flux hitting a photovoltaic panel, but what does it mean to "consume" that energy from the perspective of the emissions calculated by the Kaya identity?

To fully account for global energy use in emissions scenarios, all non-thermal sources of electricity generation, hydrogen, and process heat have traditionally been assigned a primary energy value based on some measure of the amount of fuel needed to generate equivalent amounts of secondary energy, plus the associated transmission and distribution (T&D) losses to transport the secondary energy to the customer's meter. This approach assumes that the alternative to the non-combustion energy is fossil fuel-fired combustion/generation.

For many years, this method (termed the Substitution Method) was considered in the scenario analysis community to be the "customary convention". The standard prescription for efficiency of conversion of primary to final energy in electricity generation was a constant 38.6% (Grübler and Nakicenovic, 1996; Nakicenovic et al., 1998, p.90). This convention implies a final to primary energy factor of 9.33 MJ/kWh (kWh measured at the customer's meter). For direct heat treated with the Substitution Method, a different efficiency of conversion may be used–for example, 85%, as found in IIASA's *Global Energy Assessment* (IIASA, 2012, p.1820).

One could also imagine a "dynamic substitution" approach in which non-combustion sources are assigned energy supply chain losses equal to those of the average losses in the combustion part of the energy system as they change over time. Whereas the original substitution method assumed constant losses over time, this alternative method would assess losses as they evolve in the energy systems being modeled. That means it would capture the shift from (for example) older inefficient plants to newer efficient ones.

This method of imputing average system losses to non-combustion sources has some justification when there is a significant amount of final energy delivered by fuel-based energy sources, a situation that holds now and into the near future for many energy scenarios. It also allows for accurate comparison of the contribution of both combustion and non-combustion resources to the generation mix.

There are issues with the substitution approach, however, even if

using the more accurate "dynamic" version. Imputing losses for non-combustion resources in essence creates "fictional" primary energy losses that aren't evident in the actual energy supply system. If non-combustion resources displace combustion sources with real conversion losses, those losses are eliminated and primary energy use *should* go down. Using the substitution approach masks that contribution.

In 1998, modelers participating in the landmark Special Report on Emissions Scenarios prepared for the Intergovernmental Panel on Climate Change adopted an alternative convention for non-combustion electricity generation based on the heat content of the electricity power plants delivered to the busbar. This convention equates primary energy of electricity generation to the secondary energy at the busbar, using a conversion factor of 3.6 MJ/kWh. It then subtracts T&D losses to get to final energy. The modelers adopted this method, termed *Direct Equivalence*, as their common convention in order to harmonize assumptions and facilitate the comparison of results.

SRES designated nuclear power to be treated with the direct equivalent method along with solar power, wind power, hydropower, geothermal power, and other renewable sources of electricity and hydrogen (Nakicenovic et al., 2000).[1] Hundreds of mitigation scenarios based upon the reference scenarios developed for SRES have inherited the direct equivalence assumption, and aside from cautionary notes buried deep in the SRES report itself (on pages 216 and 221) and a sidebar treatment in Nakicenovic et al. (1998, p.90), it has seldom been mentioned in the literature.

If more direct equivalent sources enter the supply mix, primary energy use will decline because conversion losses from combustion are eliminated. The substitution approach would instead indicate that total primary energy and losses in the system would change more modestly as a function of the efficiency of combustion plants remaining in the system after existing plants are displaced, a counterintuitive result. Primary Energy calculated using the direct equivalent approach correctly characterizes energy system losses over time (in the form of the Energy Supply Loss Factor).

Scenario modelers, who rely heavily on the "four-factor" Kaya identity, have often compared historical changes in the ratio of Primary Energy to GWP to the results of model projections, failing to distinguish quantitatively between changes attributable to the shift to non-combustion direct equivalent resources and those due to changes in Final Energy intensity. One example is Loftus et al. (2015), which relies on aggregate trends in Primary Energy to GWP for its otherwise rigorous scenario comparisons. Another is Peters et al. (2017), which notes the possibility of splitting out the effects of these two factors in their "methods" discussion but still shows a graph of historical and projected Primary Energy use over time (their Fig. 3).

Even if the scenario modelers understand this distinction, our experience is that policy makers can be easily misled by this way of presenting the data, thinking that scenarios with large reductions in the ratio of PE to GWP demonstrate significant end-use efficiency when in many scenarios significant savings come from increasing penetration of non-combustion resources. *This conceptual confusion is avoided by splitting those two key drivers in our expanded Kaya identity,* and we strongly caution against relying on the ratio of PE to GWP in almost all cases.

It is also important to note that two of the most important energy data agencies, the US Energy Information Administration (EIA) and the International Energy Agency (IEA), have adopted conventions about primary energy that can lead to confusion. EIA uses the dynamic substitution method for all non-combustion resources, with non-biomass renewables assigned the annual average conversion efficiency of fossil fuel plants, and nuclear power assigned the annual average thermal efficiency of nuclear plants. Electricity imports are treated using Direct Equivalence.[2] IEA treats renewables like solar, wind, and hydro using Direct Equivalence, geothermal energy as a thermal power plant with 10% efficiency, and nuclear power with the thermal efficiency of 33%.[3] These choices should be reconsidered in light of the wide acceptance of the Direct Equivalent method in the scenario modeling community and the need to avoid inconsistencies in how primary energy conversions are treated.

More research is clearly needed on methods for assessing trends in Primary Energy. As Nakicenovic et al. (1998, p.90) point out, "The very concept of primary energy becomes increasingly problematic, particularly as renewable energy forms gain importance". Appendix B delves more into the implications of correctly accounting for the convention of direct equivalence.

2.3.3. Disentangling decarbonization and fossil sequestration

Historical trends in carbon intensity expressed as a ratio of net carbon emissions (C in Equation (2)) to primary energy (PE) are unaffected by carbon sequestration because that technology has not yet entered the energy system at any detectable scale. However, making the distinction between the effects of decarbonization and sequestration is important because many energy scenarios for the 21st century that stabilize global warming at lower levels (e.g. 450 ppm CO_2 and below) imply large-scale deployment of carbon sequestration technology (Koelbl et al., 2014). The recent low-energy scenario in Grübler et al. (2018) avoids all use of sequestration, but that work is the exception.

When carbon sequestration (CS) is present in the system, the ratio of net fossil carbon emissions (NFC) to primary energy (PE) will produce misleading indications about the carbon intensity of primary energy supply. Net fossil carbon emissions from the energy sector are less than the total fossil carbon (TFC) content of primary energy supply by an amount equal to the fossil fuel carbon sequestered (CS_{FF}) rather than released to the atmosphere, as shown in Equation (4).

$$\mathrm{NFC} = \mathrm{TFC} - \mathrm{CS_{FF}} \tag{4}$$

As a result, increases in carbon sequestration artificially depress the indicator for carbon intensity in the four factor Kaya identity (C/PE), conflating two distinct effects: decarbonization, a decline in the carbon content of primary energy sources (TFC/PE), and fossil sequestration (CS_{FF}).

We can express the effect of sequestration as the ratio of net emissions released to the atmosphere (after accounting for sequestration) and the total fossil carbon dioxide in the primary energy system before sequestration (NFC/TFC). Hanaoka et al. (2006) and Kawase et al. (2006) therefore proposed adding a term to the four-factor Kaya identity that accounts for the effect of sequestration, as shown in Equation (5).

$$\frac{\mathrm{NFC}}{\mathrm{PE}} = \frac{\mathrm{TFC}}{\mathrm{PE}} \cdot \frac{\mathrm{NFC}}{\mathrm{TFC}} \tag{5}$$

where

$\frac{\mathrm{TFC}}{\mathrm{PE}}$ is the Total Fossil Carbon Intensity of Primary Energy;
$\frac{\mathrm{NFC}}{\mathrm{TFC}}$ is the Fraction emitted to the atmosphere, and
$\frac{\mathrm{TFC}-\mathrm{NFC}}{\mathrm{TFC}}$ is the Sequestration Rate, or fraction sequestered.

Without this correction, whenever the sequestration rate is rising, the carbon content-based calculation of carbon intensity (C/PE in Equation (2)) will overstate the actual decarbonization rate because

[1] It is important to clarify that engineering-economic models used to produce global energy scenarios *do* consider the technical efficiency of the engineered systems that harness non-thermal renewable resources and nuclear power. Indeed, technical efficiency is a vital characteristic of cost and performance parameters for each technology type. However, the *primary energy* data calculated for each technology type by models using SRES terms is reported in terms of direct equivalence as described above.

[2] https://www.eia.gov/tools/glossary/index.php?id=P.

[3] https://www.iea.org/statistics/resources/balancedefinitions/.

sequestration masks the carbon content of fossil fuels remaining in the primary energy mix. In other words, if the C/PE indicator is calculated using NET emissions after sequestration, the decomposition results will be misleading.

Another complexity enters when we consider sequestering carbon from the flue gases of biomass combustion. Many recent scenarios rely on biomass sequestration to achieve negative emissions (Fuss et al., 2014; Kemper, 2015), but the flow of carbon in this case is separate from those from fossil fuels. Biomass sequestration involves extracting carbon from the global biospheric carbon cycle and sequestering it. We can think of biomass sequestration as altering the additive term for land-use change included in Equations (9) and (10) below. For clarity, we show biomass sequestration as a separate term that is subtracted from the other additive components in the fully expanded decomposition below.[4]

2.3.4. Distinguishing fuel switching among fossil fuels from shifts away from fossil fuels

An additional refinement of the expanded identity is described by Peters et al. (2017) in their methods section. They advocate (and implement) further decomposition of the TFC/PE term into two terms as shown in Equation (6):

$$\frac{TFC}{PE} = \frac{PE_{FF}}{PE} \cdot \frac{TFC}{PE_{FF}} \tag{6}$$

where

$\frac{TFC}{PE}$ is the Total Fossil Carbon Intensity of all Primary Energy;
$\frac{PE_{FF}}{PE}$ is the share of Primary Energy from fossil fuels (the *fossil fuel fraction*), and
$\frac{TFC}{PE_{FF}}$ is Total Fossil Carbon Intensity of Primary Energy supplied by fossil fuels.

This additional detail allows decomposition of changes in TFC/PE into the two key drivers of those changes: switching from fossil fuels to non-combustion alternatives (e.g. from fossil fuels to zero emission energy resources) and then fuel switching among fossil fuels (e.g. from coal to natural gas, or from high to low emitting oils, as described in Koomey et al. (2016)).

A subtlety of this treatment of emissions intensity relates to the treatment of combustion of biomass and biofuels. The MESSAGE model (following the IPCC) reports CO_2 emissions from the combustion of biomass and biofuels in the agriculture, forestry, and other land-use (AFOLU) sector (IPCC, 2006). Indirect emissions of other greenhouse gases like methane are tallied separately (and lumped into the "other gases" category in Fig. 6, below).

Biomass and biofuels primary energy consumption is contained in our estimate of total primary energy consumption, but net direct carbon dioxide emissions from these fuels are captured in the AFOLU sector (along with any offsetting uptake of CO_2 in the biosphere). This is why we call our term for carbon emissions above Total Fossil Carbon and not Total Energy Carbon. Biomass and biofuels are generally small compared to total primary energy, but this accounting convention may become important in certain high biomass scenarios.

[4] In the past, biomass combustion was assumed to be carbon neutral, but more recent analysis has shown that assumption to be incorrect for biofuels (DeCicco, John M., Danielle Yuqiao Liu, Joonghyeok Heo, Rashmi Krishnan, Angelika Kurthen, and Louise Wang. 2016. "Carbon balance effects of U.S. biofuel production and use." *Climatic Change*. vol. 138, no. 3. 2016/10/01. pp. 667–680 [https://doi.org/10.1007/s10584-016-1764-4].), which points to the importance of careful accounting for carbon stocks and flows in any scenario where biomass or biofuels play a role.

3. Decomposition of emissions in the energy sector

Improvements to the Kaya Identity described in the previous section lead to new insights about the way key drivers of carbon dioxide emissions from the energy sector are affected by policy intervention. The decomposition applied in this paper incorporates each of these elements, which can be summarized as in Equation (7):

$$C_{Fossil\ Fuels} = P \cdot \frac{GWP}{P} \cdot \frac{FE}{GWP} \cdot \frac{PE}{FE} \cdot \frac{PE_{FF}}{PE} \cdot \frac{TFC}{PE_{FF}} \cdot \frac{NFC}{TFC} \tag{7}$$

where

$C_{Fossil\ Fuels}$ represents carbon dioxide (CO_2) emissions from fossil fuels combusted in the energy sector,
P is population,
GWP is gross world product (measured consistently using Purchasing Power Parity or Market Exchange Rates),
FE is final energy,
PE is total primary energy, calculated using the direct equivalent (DEq) method, as discussed above and in Appendix B,
PE_{FF} is primary energy associated with fossil fuels,
TFC is total fossil CO_2 emitted by the primary energy resource mix,
NFC is net fossil CO_2 emitted to the atmosphere after accounting for fossil sequestration.

We summarize the underlying factors (e.g., population, GWP, final energy, primary energy, primary energy from fossil fuels, and total fossil CO_2) in a dashboard as in Fig. 1, and the expanded Kaya ratios that comprise $C_{Fossil\ Fuels}$ in Fig. 2. In the first row, we show absolute values over time for each of the components, in this case for historical data from 1900 to 2014 (De Stercke, 2014). Because sequestration is negligible during this period, the graphs omit the final term in the expanded identity.

Dotted lines project the paths each driver would have followed if historic rates of change had persisted to 2014. We calculate rates of change for the periods 1900 to 2014 and 1995 to 2014. The latter period showed greater change in the final energy intensity of economic activity than the longer period. We also show those historical rates of change on the dashboards for future scenario projections, to provide benchmarks against which future scenarios can be compared.

In Figs. 1 and 2, there are three different scales at which the dashboard drivers can be plotted: absolute value, indexed value, and rate of change. Each of these provides different insights into the historical data (or, as we show later, into scenario assumptions and results).

The first tier in the dashboard shows each key driver by its absolute value. Constructing a dashboard of key drivers in absolute value terms shows decomposition results in units with physical and economic meaning (such as population, GWP, GWP/capita, or Energy Use/GWP), facilitating cross-model comparisons.

The second tier shows the relative influence of each driver in the reference case and the relative influence of the policy intervention on each driver by plotting an index relative to some base year. For Figs. 1 and 2, that base year is 1900, for graphs characterizing future scenarios below, the reference year is 2010.

The third and fourth tiers show the growth rate for each factor. The instantaneous growth rate of total carbon dioxide emissions is equal to the sum of the growth rates for each key factor, as shown in Equation (8a) (for derivation, see Appendix I).

$$\frac{d(C)/dt}{C} = \frac{d(P)/dt}{P} + \frac{d(GWP/P)/dt}{GWP/P} + \frac{d(FE/GWP)/dt}{FE/GWP} + \frac{d(PE/FE)/dt}{PE/FE} + \frac{d(PE_{FF}/PE)/dt}{PE_{FF}/PE} + \frac{d(TFC/PE_{FF})/dt}{TFC/PE_{FF}} + \frac{d(NFC/TFC)/dt}{NFC/TFC} \tag{8a}$$

Since we calculate changes over discrete time periods, this

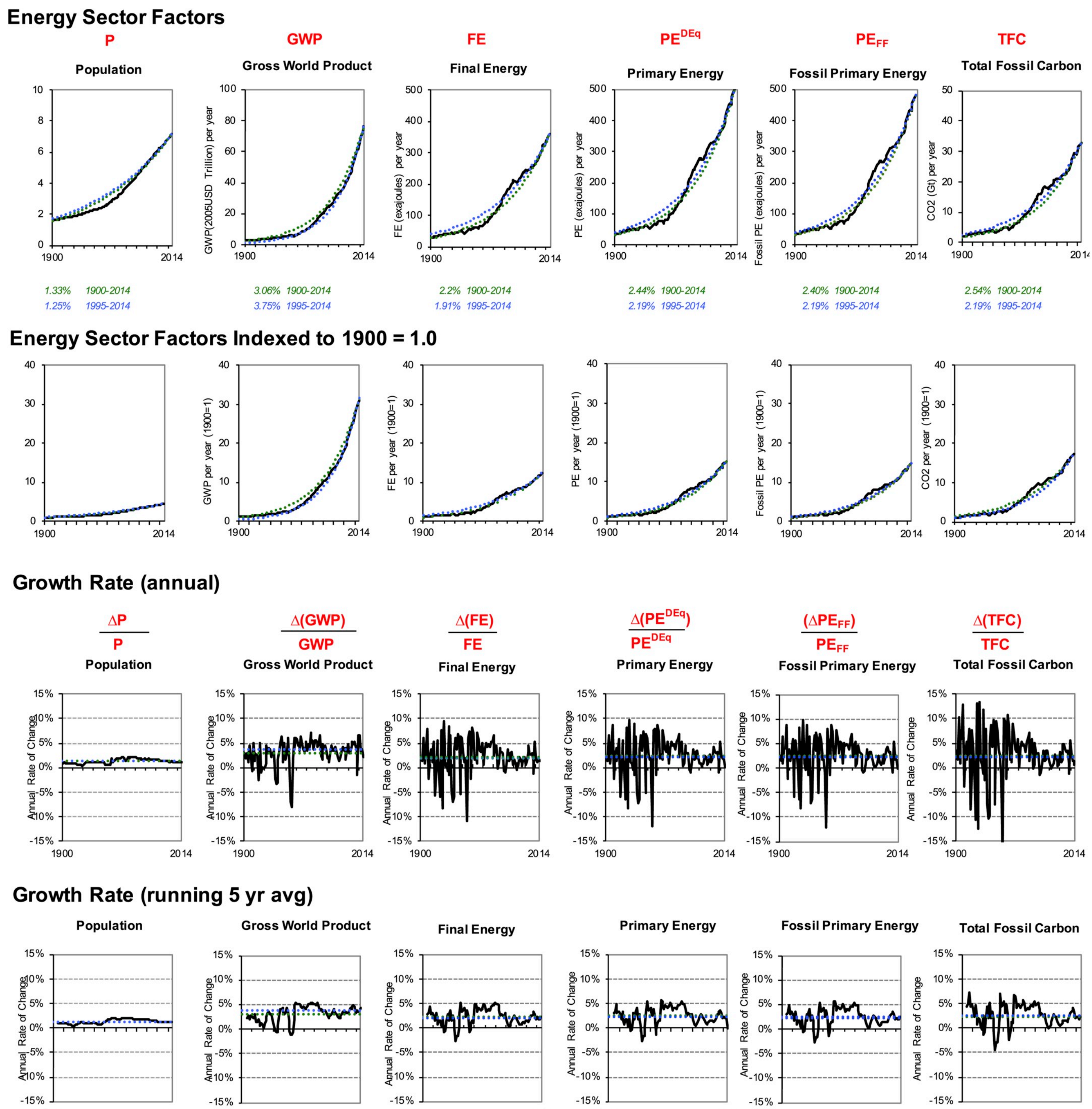

Fig. 1. Dashboard of key factors–Historical data 1900 to 2014.
Data for 1900 to 2014 taken from IIASA's PFU database: De Stercke (2014) and http://www.iiasa.ac.at/web/home/research/researchPrograms/TransitionstoNewTechnologies/PFUDB.en.html. Green and blue dotted lines represent historical average annual rates of change for 1900 to 2014 and 1995 to 2014, respectively. GWP data are based on Purchasing Power Parity (PPP). PE is measured using direct equivalence (DEq) for non-combustion sources. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

relationship holds as an approximation:

$$\frac{\Delta(C)}{C} \approx \frac{\Delta(P)}{P} + \frac{\Delta(GWP/P)}{GWP/P} + \frac{\Delta(FE/GWP)}{FE/GWP} + \frac{\Delta(PE/FE)}{PE/FE} + \frac{\Delta(PE_{FF}/PE)}{PE_{FF}/PE} + \frac{\Delta(TFC/PE_{FF})}{TFC/PE_{FF}} + \frac{\Delta(NFC/TFC)}{NFC/TFC} \tag{8b}$$

For historical data, we show the growth rate in the third tier with year-by-year changes, and for the fourth tier, we show it with data tallied as a running five-year average. The annual growth rate shows more variation in the historical data, as we expect. For future scenario projections, we show data averaged over ten-year periods, because those are the data available in the scenario databases we use.[5]

[5] One subtlety is that for future scenarios we calculate compound annual growth rates over ten-year periods then apply those growth rates in each year of the relevant period. This allows us to plot trends over the entire analysis period

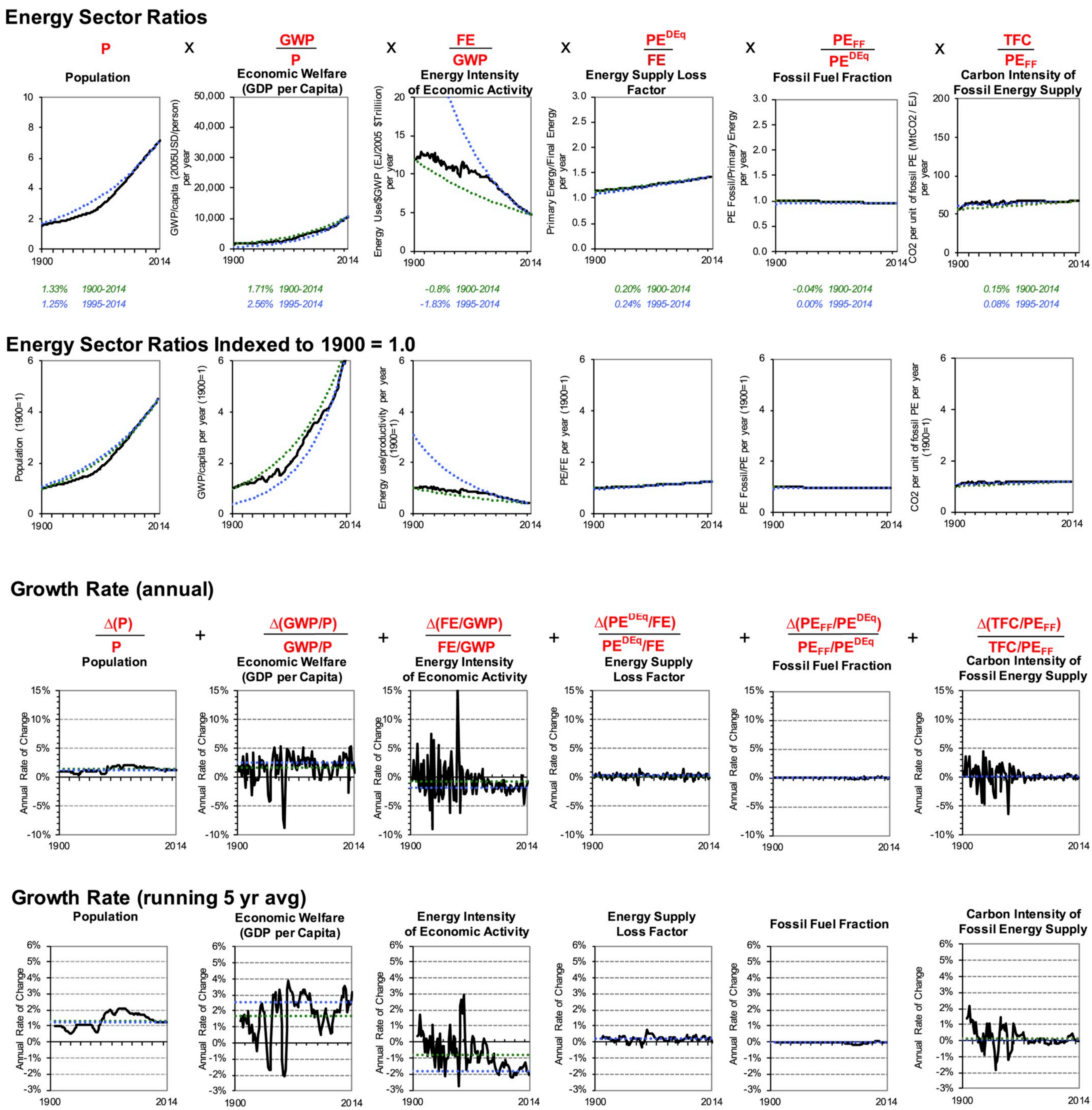

Fig. 2. Dashboard of key driver ratios–Historical data 1900 to 2014.
Data for 1900 to 2014 taken from IIASA's PFU database: De Stercke (2014) and http://www.iiasa.ac.at/web/home/research/researchPrograms/TransitionstoNewTechnologies/PFUDB.en.html. Green and blue dotted lines represent historical average annual rates of change for 1900 to 2014 and 1995 to 2014, respectively. GWP data are based on Purchasing Power Parity (PPP). PE is measured using direct equivalence (DEq) for non-combustion sources. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Interestingly, Fig. 1 shows that GWP growth is greater in the past two decades than from 1900 to 2014 but the annual rate of increase in final energy consumption is lower in the later period. Final energy intensity reductions have therefore accelerated in the past two decades.

(footnote continued)
(rather than dropping a decade in the beginning or at the end as we would have to do if we showed only one growth rate per decade). If scenario output data are available for intervening years, then this convention can easily be altered.

We use this same format for scenario projection data. To illustrate, we show example dashboards for a scenario projection using the MESSAGE 4.0 model, based on results presented in the AMPERE modeling exercise (see Appendix H and Riahi et al. (2015)). We chose MESSAGE as the exemplar in this article because the MESSAGE modeling team is widely known and respected in the modeling community, and because MESSAGE explicitly treats almost all warming agents in its projections, thus allowing us to present a full decomposition to

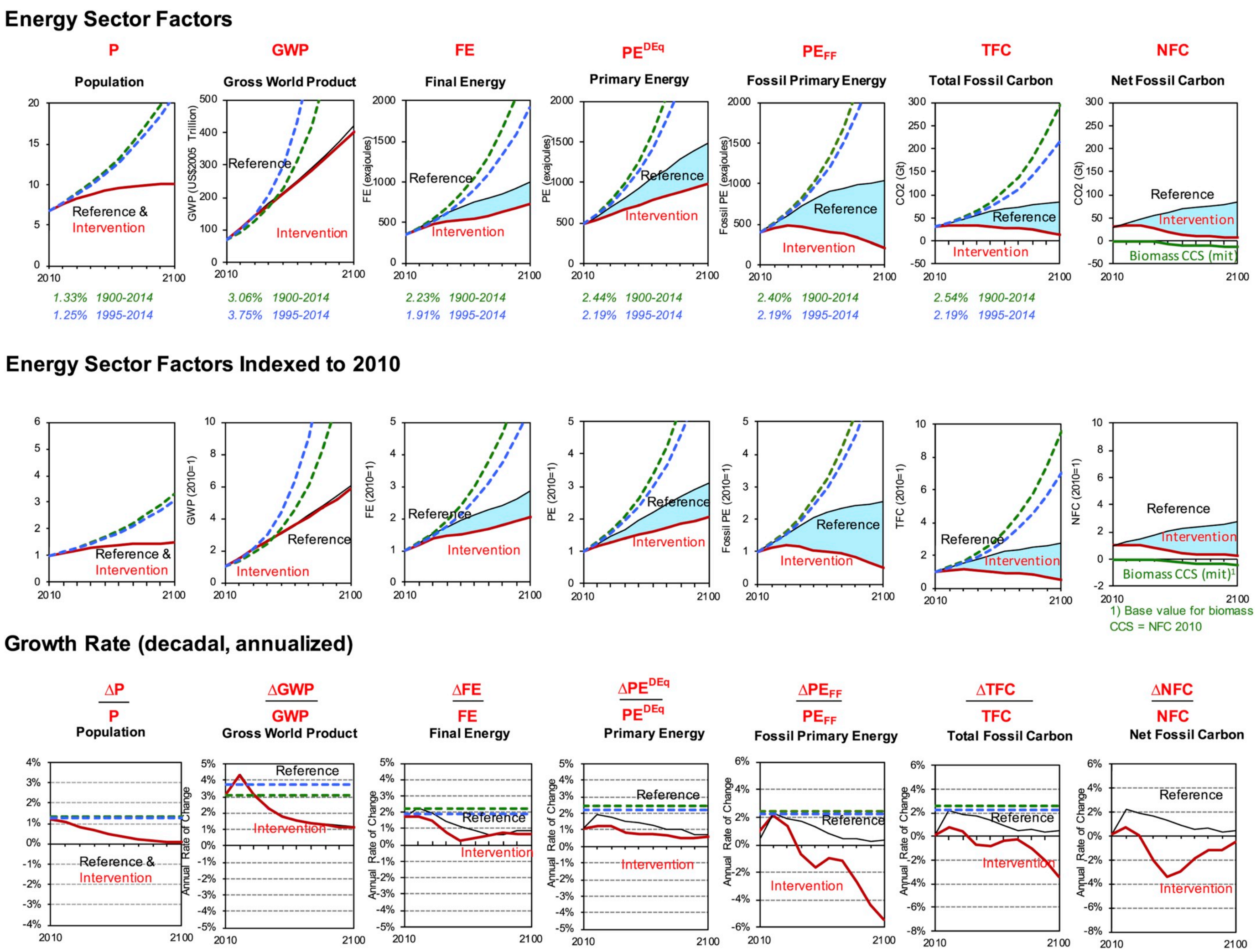

Fig. 3. Dashboard of key factors driving a future scenario projection.
Model: MESSAGE 4.0, full technology cases, base case OPT and 450 ppm OPT cases, from the AMPERE 2 database: Riahi et al. (2015) and https://tntcat.iiasa.ac.at/AMPEREDB. Green and blue dotted lines represent historical average annual rates of change for 1900 to 2014 and 1995 to 2014, respectively. GWP data are based on Purchasing Power Parity (PPP). PE is measured using direct equivalence (DEq) for non-combustion sources. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

illustrate our calculations and visualizations (Fricko et al., 2017; Krey et al., 2016; Schrattenholzer, 1981).

Fig. 3 shows the underlying factors for the MESSAGE scenario, while Fig. 4 shows the Kaya ratios, just as for the historical data. The figures show the reference scenario using a black solid line and the low emissions (intervention) scenario as a red line. The dashed lines show trends in historical data for comparison as discussed above.

In the NFC absolute value pane, we also show the total effect of biomass CCS plus fossil CCS as a green solid line. Even though negative emissions from biomass CCS are not counted in the energy sector, its deployment is linked to the energy sector as well as to the carbon cycle associated with land use. Because this emissions reduction option is important in many low emissions scenarios (Kemper, 2015), we add this line to show how it compares to the NFC in the intervention case. We also show a line for biomass CCS in the dashboard of additive terms, below.

Fig. 3 shows some key insights. Population, GWP, and carbon intensity of fossil energy are not much affected by the intervention scenario, while final energy, primary energy, fossil fuel fraction, and net fossil carbon are all significantly reduced in the intervention case. Growth rates for all factors in the future scenarios are lower than historical rates.

GWP growth rates decline over the analysis period, but final energy growth slows almost to zero then starts rising again after 2050, causing the FE/GWP ratio in Fig. 4 to break off from the 1995 to 2014 trend line and slow its long and rapid decline. This curious behavior is ripe for further investigation, and it illustrates the kind of questions that this method of presenting results enables (see also Appendix C).

The figures also show the importance of fossil CCS to reducing emissions in the intervention case. The NFC pane in Fig. 3 clearly shows an emissions reduction compared to the TFC pane, and the NFC/TFC pane in Fig. 4 shows the importance of that reduction relative to TFC emissions.

The factors dashboard and the ratios dashboard are a starting point for further investigation. Now let's dig into additional ways to garner insights from this analysis and presentation approach.

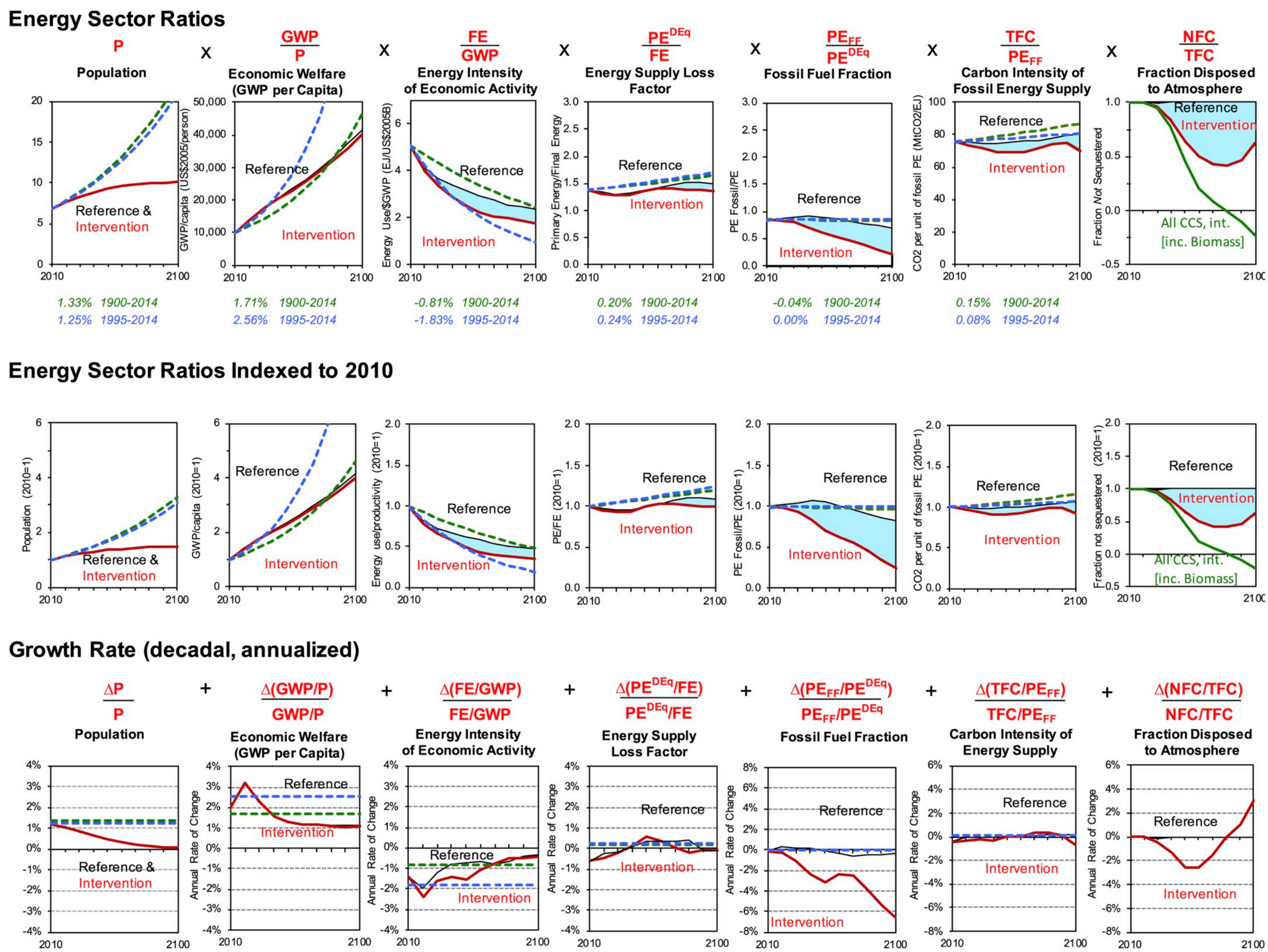

Fig. 4. Dashboard of key Kaya driver ratios for a future scenario projection.
Model: MESSAGE 4.0, full technology cases, base case OPT and 450 ppm OPT cases, from the AMPERE 2 database: Riahi et al. (2015) and https://tntcat.iiasa.ac.at/AMPEREDB. Green and blue dotted lines represent historical average annual rates of change for 1900 to 2014 and 1995 to 2014, respectively. GWP data are based on Purchasing Power Parity (PPP). PE is measured using direct equivalence (DEq) for non-combustion sources. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

4. Another window into the expanded kaya results

Another way to visualize changes in emissions over time is with a bar chart. This type of graph shows the compound annual growth rate for each term in the expanded Kaya identity over some time period, based on Equation (8b). As shown in Fig. 5, it can be plotted for the reference case, an intervention case, or the difference between them, giving a quantitative indication of the contributors to emissions growth or reductions, in this case over the 2010 to 2100 time-period.

Fig. 5 shows results for our exemplar MESSAGE scenarios. Changes in GWP per capita and final energy per unit of GWP are the two most important drivers of emissions trends in the reference case, while reduction of fossil fuel fraction (decarbonization of the primary energy supply using non-fossil options), fossil sequestration, and the final energy intensity of economic activity are the three most important components of emission reductions in the intervention case.

5. Additive elements for non-energy emissions

The expanded Kaya identity in this article addresses direct carbon dioxide emissions from the energy sector. Now we turn to other sources of greenhouse gas emissions, including CO_2 emissions from industrial processes like cement production, CO_2 emissions from land-use changes such as deforestation, and non-CO_2 greenhouse gases, which include methane, nitrous oxide, and a set of powerful greenhouse gases containing fluoride manufactured for human use.[6]

These factors are included in the third dashboard as additional sources of emissions, with the non-CO_2 gases being converted to carbon dioxide equivalent. Total greenhouse gas equivalent emissions (C^{eq}_{Total}) can be expressed as in Equation (9).

$$C^{eq}_{Total} = C_{Fossil\ Fuels} + C_{Industry} + C_{Land-use} + C^{eq}_{Non-CO2\ gases} - CS_{Biomass} \tag{9}$$

where

$C_{Industry}$ represents carbon dioxide emissions from industrial processes (non-energy uses of fossil fuels that result in emissions, such as cement and aluminum production). Some models combine these

[6] The so-called F-gases include: hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), and sulfur hexafluoride (SF6), all of which are released in extremely small quantities compared to carbon dioxide, but the warming potential of each molecule can be as much as five orders of magnitude greater.

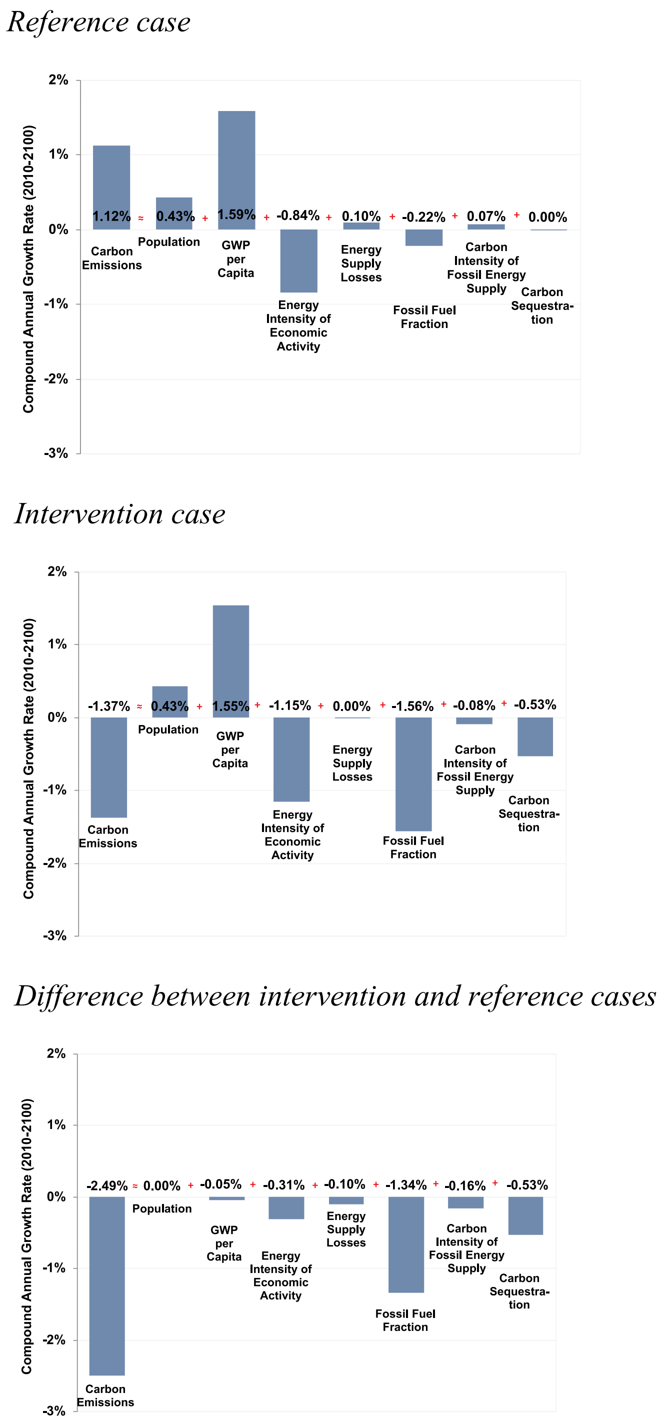

Fig. 5. Compound annual growth rate in expanded Kaya drivers (MESSAGE, 2010 to 2100).
Model: MESSAGE 4.0, full technology cases, base case OPT and 450 ppm OPT cases, from the AMPERE 2 database: Riahi et al. (2015) and https://tntcat.iiasa.ac.at/AMPEREDB.

emissions with fossil fuel combustion emissions, but they should be split out for clarity.

$C_{Land-use}$ represents net carbon dioxide emissions from changes in agriculture and land-use that are not associated with emissions reductions from biomass CCS. This term can also be negative if there is significant reforestation.

$C^{eq}_{Non-CO_2\ gases}$ represents emissions of other greenhouse gases converted to CO_2 equivalent using relative factors of global warming potential.[7]

$CS_{Biomass}$ represents net negative emissions from sequestering carbon emissions associated with biomass combustion (in effect, such sequestration removes carbon from the biosphere). The emissions reductions from this source must be carefully distinguished from those land-use changes.

The guiding principle should be that *all* energy system and related emissions should be included in one of the additive terms in Equation (9). For example, indirect emissions from hydroelectric facilities would include CO_2 from fossil energy used in constructing the plant (in the fossil fuels category), CO_2 from cement used in construction (in the industry category), and methane emissions from decomposition of biomass on flooded land (in the non-CO_2 gases category). For nuclear power, indirect emissions from fossil-powered enrichment would fall into the fossil fuels category, while CO_2 from cement used in construction would fall into the industry category.

Substituting $C_{Fossil\ Fuels}$ with the expanded Kaya identity components from Equation (7), we get Equation (10), which is what we call our *fully expanded decomposition*:

$$C^{eq}_{Total} = P \cdot \frac{GWP}{P} \cdot \frac{FE}{GWP} \cdot \frac{PE}{FE} \cdot \frac{PE_{FF}}{PE} \cdot \frac{TFC}{PE_{FF}} \cdot \frac{NFC}{TFC} + C_{Industry} + C_{Land-use} + C^{eq}_{Non-CO_2\ gases} - CS_{Biomass} \quad (10)$$

Standard scenario outputs for models with comprehensive coverage of emissions will usually include the data for each additive term. In some cases, additional calculations or data outputs will be required.

The fully expanded decomposition of key drivers in Fig. 6 has all additive elements: net fossil energy CO_2 emissions, biomass sequestration, land-use change, industrial non-energy CO_2 emissions, and non-CO_2 gas emissions. If direct air capture of CO_2 becomes important in future, another pane with those emission reductions can be included in the additive dashboard.

Energy sector emissions reductions still dominate all reductions, but each of the additive components has a measurable effect on total greenhouse gas emissions.

Appendix J gives details on the projection of cement emissions, which are combined with fossil energy emissions in the MESSAGE model outputs. We derive them instead from van Ruijven et al. (2016) and subtract from the total of fossil energy and industrial emissions from the MESSAGE outputs to get fossil fuel energy emissions.

It is critical to separate biomass CCS from fossil CCS in such attribution graphs to get a clear picture of carbon flows. As discussed in section 2, above, biomass CCS extracts carbon from the atmosphere and sequesters it, while fossil CCS sequesters emissions that otherwise would have reached the atmosphere from the combustion of fossil fuels.

The importance of CCS is highlighted in Fig. 7, which gives the full picture of CCS compared to TFC and NFC (it includes the energy sector plus biomass CCS, but not the other additive terms in Fig. 6). The reference case TFC is in black and the intervention case TFC is in red. NFC (which shows the effect of fossil CCS on TFC) is represented by the blue solid line, and NFC minus biomass CCS is shown by the solid green line.

[7] We convert emissions of the two major non-CO_2 greenhouse gases (methane and nitrous oxides) to CO_2 equivalents using 100 year global warming potentials (including climate feedbacks) from IPCC. 2013. *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)]*. Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press. [http://www.climatechange2013.org], Chapter 8, table 8.7, page 714: https://www.ipcc.ch/pdf/assessment-report/ar5/wg1/WG1AR5_Chapter08_FINAL.pdf. For the MESSAGE analysis, we use the model's calculation of the GWP of F-gases.

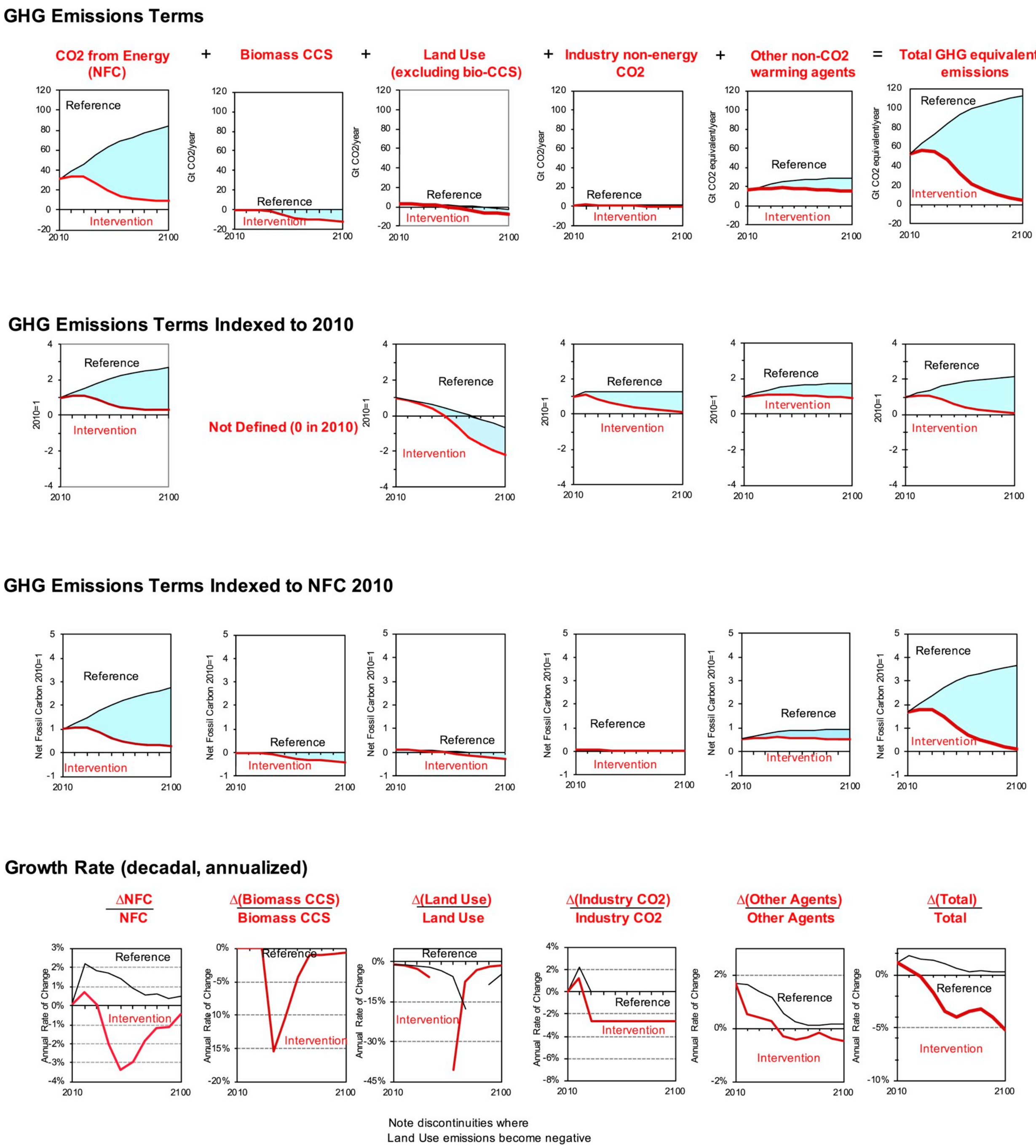

Fig. 6. Summarizing effects of all key drivers on total emissions (MESSAGE).
Model: MESSAGE 4.0, full technology cases, base case OPT and 450 ppm OPT cases, from the AMPERE 2 database: Riahi et al. (2015) and https://tntcat.iiasa.ac.at/AMPEREDB. Industrial non-energy CO_2 emissions (e.g., cement process emissions) taken from Appendix J.

The emissions reductions associated with fossil and biomass CCS are shown in the dotted blue and green lines, respectively.

Reductions in direct emissions from the energy sector are represented by the difference between the black and red lines in Fig. 7, then savings from CCS contribute further. Fossil CCS has a slightly larger cumulative impact than biomass CCS over the analysis period, but both achieve reductions of Gigatonne scale, so are significant by any measure. The decline in fossil CCS reductions is significant after 2070, a result that points to the need for further digging into these output results.

Another way to present the full emissions reductions picture is shown in Fig. 8. This chart shows total GHG equivalent emissions in the reference and intervention cases, then attributes savings to each component we've identified in the energy sector ratios dashboard (Fig. 4) and the additive emissions dashboard (Fig. 6).

The non-energy emissions results in the additive dashboard come straight from model outputs in almost all cases. To decompose the fossil energy related emissions (which are part of a multiplicative identity), we rely on the LDMI I technique first proposed by Ang (2004). This method gives a perfect decomposition (no residual term) and is relatively simple to apply to multi-factor problems. In addition, the IEA uses the LMDI I method to decompose CO_2 emissions from electricity production (IEA, 2015), creating a credible precedent for our choice.

Population projections are the same in both the reference and intervention cases, so no emissions savings accrue from this category in this scenario (or in most other scenario exercises (Bongaarts and Neill,

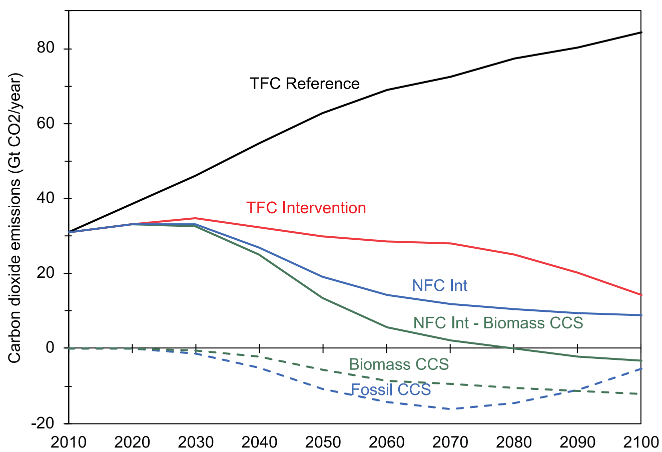

Fig. 7. Summarizing the effects of fossil and biomass CCS on the MESSAGE scenarios.

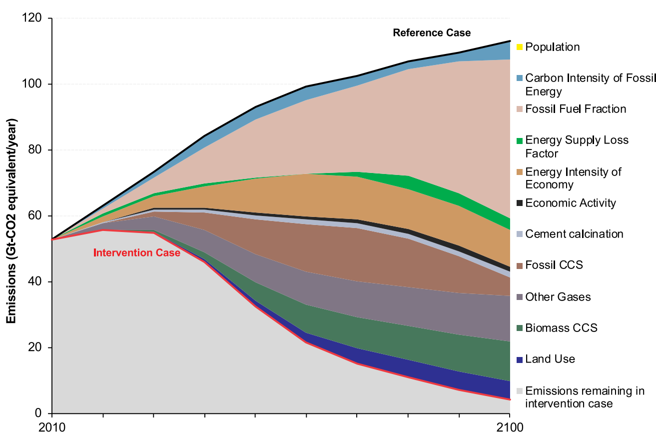

Fig. 8. Summarizing effects of all key drivers on total emissions (MESSAGE).

2018)). The majority of the decline in Total Fossil Carbon is from substituting non-combustion resources for fossil energy supply. Fuel switching among fossil fuels contributes only a nominal amount to emissions reductions. In addition, substitution on the supply side is the single largest contributor to emissions reductions for the whole scenario. The contribution of Fossil CCS declines in the latter part of the analysis period, as we also saw in Fig. 7.

Graphs like Fig. 8 work well in plotting contributions to emissions reductions, but when one or more terms in the identity result in an increase in emissions over time a stacked area graph can't show that easily. For example, the Energy System Loss Factor (ESLF) sometimes increases during part of the intervention scenario, thus increasing emissions during that period. In those cases, we adjust for that increase in those years by allocating it in proportion to the emissions reductions from the other terms in the fully expanded decomposition in every year. The sum of all net emissions reductions will then reflect the difference between the reference case (black line) and the intervention case emissions (red line). The sign of each term (positive or negative) can be most accurately represented in bar charts like those in Fig. 5.

6. Benefits and uses of decomposition methods

The decomposition tools described in this article offer benefits over the ad hoc methods traditionally used in the scenario analysis community. Individual modeling groups often develop their own techniques, but those cannot be easily applied for cross-model comparisons and are normally not as comprehensive as those developed in this article. For example, most analysts still rely on the four factor Kaya identity for analyzing scenario results, which can lead to confusion, as we describe above.

There are three main audiences for decomposition methods: modelers, policy analysts, and research funders. Each of these groups can use decompositions for sanity checking, promoting transparency, and making valid comparisons.

6.1. Sanity checking during scenario creation

For modelers (and secondarily, policy analysts and funders who review interim results), these tools allow scrutiny to begin much earlier in the research cycle and encourage sanity checking of assumptions and results before publication. For example, scenarios often rely on heroic assumptions for costs and adoption of new exotic technologies (like biomass CCS) combined with modest projected changes in FE/GWP or renewable energy adoption. While not necessarily wrong, such inconsistencies in relative technological progress should prompt further digging and analysis (Hummel, 2006). Use of these decomposition methods makes that analysis easier and quicker.

6.2. Promoting transparency

For all users, decomposition tools allow greater transparency, understanding, and documentation of methods and results than has heretofore been possible. The assumptions and algorithms of these models can be opaque, but decomposition methods give a view into the black box that will enable debate about key issues and uncertainties in mitigation scenarios, even though the complex algorithms embedded in the models are not as easily subject to outside scrutiny.

6.3. Making valid comparisons quickly

For all users, decomposition tools allow better comparisons between history and projections, baseline and policy cases, and different baseline and policy cases from many modeling shops (Hummel, 2006). For example, a substantial divergence of a projection from historical trends (or unintuitive discontinuities in the projection) can reveal issues with data and methods or lead to new policy insights.

Comparisons among different projections can be done at a glance using our decomposition dashboard and supporting graphs. Each scenario set can be summarized in a few pages, and the results of multiple models can be quickly compared. It is now almost never possible to do such comparisons easily using published modeling results, but if modelers create decompositions using standard tools in a consistent framework, it will become standard practice.

7. Limitations of the analysis and areas for further research

The decomposition of key drivers involves examination of high-level, aggregate data. The focus on global trends can obscure important changes at the regional and sectoral levels, as well as technological trends.

An obvious next step is to apply the dashboard and associated tools to compare recent model runs completed for IPCC's latest assessment report and follow-on exercises (Riahi et al., 2017). The tools created for this article can readily be applied to multiple scenarios, and we make them freely available at http://www.koomey.com for modelers who want to apply them. We are also eager to help modelers implement key scenarios in this framework, so we can learn more and improve the tools.

It is also time for a comprehensive review of the variables included in scenario databases, in light of the data needs for the decomposition methods outlined in this article. Certain key information for most models, like the split between fossil, biomass, and industrial process CCS impacts, and the split between fossil energy and industrial process carbon dioxide emissions, still require additional digging or

assumptions to create these decompositions. Small changes in the required output data could facilitate more rapid creation of many decomposition analyses. Appendices D, E, and F present some specific examples of how we use data from the Ampere and AR5 scenario databases and give suggestions for additional data that should be included to make creating full decompositions easier.

One area that has been insufficiently explored to date is the set of interdependencies between the different terms in multiplicative identities, first pointed out for the IPAT identity by Ehrlich and Holdren (1971) and explored in some depth for the four-factor Kaya identity by Nakicenovic et al. (2000). The identity implies that each term is independent of the others, but in practice, that is not a good assumption. For example, population growth and technological development are both affected by the level of wealth per person, and these factors interact. If you change one factor, the others will also change. These complexities are beyond the scope of this analysis, but assessing those interactions empirically is a worthwhile focus of additional research, starting with assessing correlation coefficients among the terms.

The decomposition of key drivers presents little information about the energy technologies that are underlying the emissions scenario, or more importantly, how that portfolio of energy technologies is affected by climate policy intervention. A more detailed decomposition of sources of mitigation is required to illuminate those insights at the technology level, as explained in Hummel (2006).

The treatment of biomass and biofuels combustion in IPCC-related scenarios (lumping these emissions into the AFOLU sector) may be worth revisiting. An alternative way to treat emissions from these fuels would be to include the direct carbon emissions from biofuels in the emissions from the energy sector (along with the indirect CO_2 emissions from collection and processing of these fuels, which are already tallied there and in the “land use” sector), and to include the uptake of carbon emissions associated with growing biomass for combustion and conversion to biofuels in the “land use” pane in Fig. 6. The term for Total Fossil Carbon would then be renamed “Total Energy-sector Carbon”, or TEC, to capture this change. The advantage of this treatment is more specificity in which sectors the emissions and uptake occur.

Direct air capture of carbon dioxide has attracted attention recently as a long-term option for emissions reductions (APS, 2011; Sanz-Pérez et al., 2016). If this option ever becomes important in mitigation scenarios, the additive dashboard (Fig. 6) will need another pane to account for those impacts. If the use of synthetic methane (Porosoff et al., 2016), in which carbon is extracted from the atmosphere then combined with hydrogen derived from non-fossil sources, ever becomes commonplace, the direct emissions from using such fuels would also reside in the energy sector, while the carbon uptake from creating those fuels would reside in the new “direct air capture” pane of Fig. 6.

8. Conclusions

The energy scenario community has struggled for decades with how best to compare and contrast analysis results. This article presents one way to solve that problem that builds upon the familiar Kaya and IPAT identities. The graphs developed here show the key drivers of emissions growth and reductions in a standard format using scenario outputs that are widely available. We are hopeful that adoption of these methods will result in better understanding of scenario results and more rapid learning in the analysis community than has prevailed to date.

Declaration of interests

None. Authors completed this article on their personal time, without support from funding agencies in the public, commercial, or not-for-profit sectors.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.envsoft.2018.08.019.

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